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MegaSense: Cyber-Physical System for Real-time Urban Air Quality Monitoring

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***Abstract*—Air pollution is a contributor to approximately one in every nine deaths annually. To counteract health issues resulting from air pollution, air quality monitoring is being carried out extensively in urban environments. Currently, however, city air quality monitoring stations are expensive to maintain, resulting in sparse coverage. In this paper, we introduce the design and development of the MegaSense Cyber-Physical System (CPS) for spatially distributed IoT-based monitoring of urban air quality. MegaSense is able to produce aggregated, privacy-aware maps and history graphs of collected pollution data. It provides a feedback loop in the form of personal outdoor and indoor air pollution exposure information, allowing citizens to take measures to avoid future exposure. We present a battery-powered, portable low-cost air quality sensor design for sampling $PM_{2.5}$ and air pollutant gases in different micro-environments. We validate the approach with a use case in Helsinki, deploying MegaSense with citizens carrying low-maintenance portable sensors, and using smart phone exposure apps. We demonstrate daily air pollution exposure profiles and the air pollution hot-spot profile of a district. Our contributions have applications in policy intervention management mechanisms and design of clean air routing and healthier navigation applications to reduce pollution exposure.**

***Index Terms*—Air quality, Cyber-physical Systems, Internet of Things, Low-cost sensors, Data integration and visualization.**

I. Introduction and Background

Air pollution is a growing concern with an increasing number of acute air pollution episodes worldwide [1], [2]. As a result, data on air quality is becoming increasingly available[1,2,3] and the science underlying the related health impacts is also evolving rapidly. To date, air pollution – both ambient (outdoor) and household (indoor) – is considered the biggest environmental risk to health, carrying responsibility for about one in every nine deaths annually [3]. In response, many cities commit to a network of stations that monitor air quality in real-time. However, the high costs of installation and maintenance of these stations results in a sparse monitoring [4], satisfying the legislative requirements but not providing information about localized air pollution important to health protection [5].

Urban air is an umbrella concept, combining outdoor and indoor air [6]. In addition to spatial and temporal variability of outdoor concentrations, the indoor environment plays a significant role in personal exposure to air pollution [7]. Indeed, urban populations spend large fractions of their time throughout life. For example, in European cities people spend on average about 80–90% of their time indoors, 1–7% percent in a vehicle, and only 2–7% outdoors [8]. Indoor environments represent important micro-environments when addressing personal exposure to air pollution in urban environments.

Cyber-physical systems (CPS), defined as networked intelligent systems embedding sensors, controllers and actuators designed to interact with the physical world, have emerged as a powerful solution for monitoring the urban environment. Examples of CPS adoption include real-time management in the urban water cycle [9]; smart buildings for energy efficiency [10]–[12]; and smart manufacturing and industry 4.0 [13]. Building on advances in Internet of Things, air quality can now be monitored with low-cost consumer-grade sensors [14], enabling designing powerful CPS which aggregate measurements and use them to determine, e.g., air pollution measurement coverage and local pollution hot-spots. This enables taking actions such as:

1) Warning citizens to avoid certain areas and times in different micro-environments;
2) Detecting patterns in pollution over time to predict healthier routes with least pollution exposure for individuals;
3) Preventing pollution hot-spot formation by recommending routes that spread vehicle pollution instead of concentrating it;
4) Motivating drones, autonomous vehicles, and citizens carrying personal air quality sensors to monitor areas that lack coverage.

In this paper, we present the design, development and deployment of the MegaSense cyber-physical system for monitoring urban air quality. MegaSense is the first end-to-end system providing coverage of air pollution exposure in different urban micro-environments to be used continuously throughout the day. Previous system research has focused on improving coverage of specific parts of the monitoring infrastructure. Mainly on the performance of low-cost sensors [5], calibration of low-cost sensors [15], providing on-line platform services [16] with downloadable Apps, and development of indoor air quality supervision systems [17]. In contrast, MegaSense provides opportunities to improve both policy making and the engagement of citizens. Our contributions are as follows:

[1]https://www.hackair.eu/open-air-quality-datasets/
[2]https://www.eea.europa.eu/themes/air/explore-air-pollution-data
[3]https://index.okfn.org/dataset/emissions/

- MegaSense, a cyber-physical system design for federated air-quality sensing using crowd-sourced data;
- A battery-powered, portable low-cost air quality sensor design, tested in Helsinki by 100 volunteers;
- Analysis and demonstration use cases of resulting air quality measurements.

II. MegaSense System Model

Figure 1 gives an overview of the MegaSense system architecture. The system receives data from sensing platforms measuring local pollution exposure and other variables affecting it. This data is processed into air quality information such as maps and advice on how to reduce personal exposure, take healthier routes, and direct participants to improve measurements in areas that have limited sensor coverage. Below we detail the different components of the system architecture.

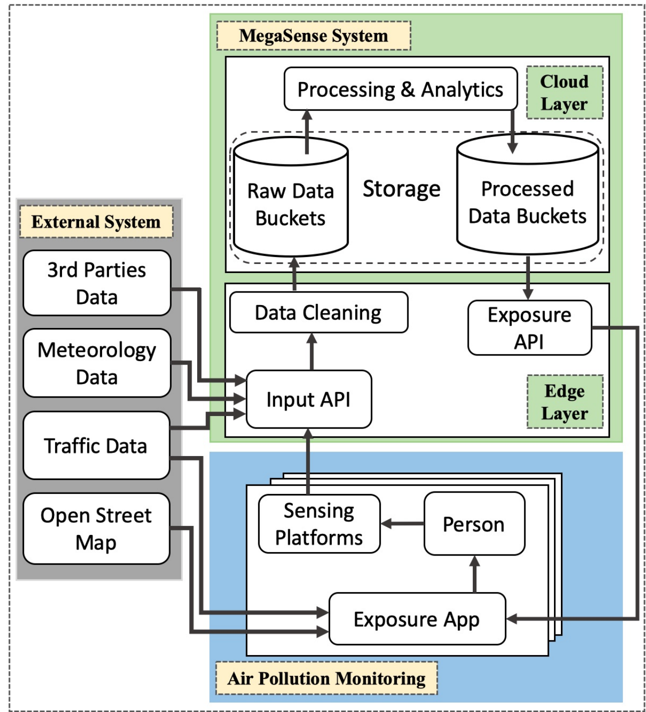

Figure 1: MegaSense Cyber-Physical System.

A. *MegaSense Core*

The core of MegaSense consists of two layers: the *Edge* and *Cloud*. The *Edge* layer is responsible for reactively receiving data from available data sources, such as sensor devices, traffic data systems, and weather information systems. It delivers advice and pollution maps to the mobile *Exposure App* which provides the user with personal air pollution exposure information as well as district exposure maps.

This layer is responsible for data preprocessing for filtering and data cleaning. The data is then placed in long-term storage for the use of the *Cloud* layer. The data input API is generic, and can support all types of environmental data. The pre-processing components are deployed at the edge of the network in order to increase the scalability of the system, e.g. by doing initial aggregation and removing erroneous values, and therefore reducing data pressure and bandwidth requirements. The same edge layer can be run on multiple ”edges”, such as districts, 5G network towers, and shopping malls. This will improve coverage and allow citizens to use local data when available. The *MAP API* serves up maps based on latest results of the analytics from the large scale storage, or a local cache, to the *Exposure App*.

The *Cloud* layer is responsible for storing cleaned data and aggregating the crowd-sourced data while preserving the privacy of participants. It includes a scalable storage system based on Lustre, a distributed production-grade file system similar in principle to Amazon S3. MegaSense does not mandate the use of a particular storage system, and is compatible with any system implementing a POSIX File System API.

Raw and processed data are stored in *buckets*, representing different datasets for the purposes of separation of concern, access control, and privacy. MegaSense permissions to access or upload data can be controlled on a per-bucket and per-user basis. The data is collected and stored as raw data in JSON format. Each authorized entity is given an access key with access to the required buckets, and which can be revoked, in case it falls into the wrong hands.

The processing and analytics of the Cloud layer generate maps with aggregated pollution measurements, so that individual measured locations are not revealed. It takes into account vector information such as distance between sensor devices, so data is processed individually as a spatially aggregated time series. Aggregates such as blocks, districts will get air quality estimates this way. In addition, crowd-sourced sensor data is improved through on-line calibration [15]. The system combines crowd-sourced data with traffic information and 3rd party data sources to provide users a holistic view of current pollution hot spots and nearby pollution sources.

B. *External Systems*

External data is pulled to the rest input API from open sources such as weather data from National Meteorological institutions, city reference station air pollution data from municipal bodies for sensor data calibration, traffic data from city info sharing services, and geo-spatial applications such as OpenStreetMaps. Third parties, such as business entities and other researchers, can also supply or retrieve data and results through the Input and Exposure APIs. In the current research deployment data upload and access by third parties[4], the Input and Exposure APIs (Figure 1) are called Write and Read, respectively.

C. *Air Pollution Monitoring and Exposure App*

To monitor air pollution at the personal and local level, citizens can use a mobile app to see current and predicted air quality conditions. Citizens can also carry a portable sensor device [18], allowing for a much more accurate picture of their personal exposure to pollutants. These portable sensor devices include meteorological variables such as temperature, relative humidity (percent) and wind speed, and air pollutants

[4]https://megasense-server.cs.helsinki.fi/

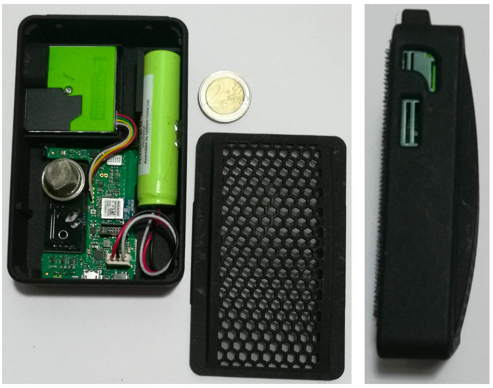

Figure 2: Hope Sensor.

such as particulate matter ($PM_{2.5}$ and PM_{10}), and gases (NO_2, CO and O_3). In addition, the sensor device can interact with the smartphone, allowing for collections of rich sensor data to determine other factors that affect pollution exposure, such as the location of the measurement, whether the user is indoors or outdoors, and the type of vehicle being used.

As the citizens pass through micro-environments such as indoors, in transit, outdoors, the exposure caused in these micro-environments is measured by the sensing platform. This data is processed by MegaSense and delivered to the *Exposure App*, which shows instantaneous personal exposure, exposure over time, as well as a pollution map for route planning.

III. Portable Air Quality Sensor Design

To provide citizens a convenient and affordable method to measure their exposure to air pollution, the University of Helsinki designed a new sensing platform based on a BMD-340 System on a module and mobile phone app called HOPE sensor (Figure 2). The platform connects to COTS Android smartphones over Bluetooth Low Energy, and the smartphones report their readings further to a collecting server. The sensor model for measuring the PM is a Sensirion SPS30. For a list of all the sensor components available on the device, see Table I. The platform is powered with a 3500mAh battery and enclosed in a 3D-printed case made of ESD-PETG filament. The form dimensions are: width 75 mm, depth 33mm, height 127 mm, with weight 165 grams. The front is protected by an aluminium mesh. General battery life before recharging via micro USB interface: 26 hours. Indicator LEDs are used for communication and charging. Simple maintenance to clean away dust can be performed using pressurised air. Compared to our previous prototype [19], this sensor is portable and considerably lighter.

Table I: Sensors available in the units.

Sensor	Type	Cycle Timer
BME-280	Temp, Humidity, Air Pressure,	1
Battery	Voltage	2
Sensirion SPS30	PM	3
SI1133-AA00-GM	UV	4
MiCS-4514	CO, NO_2	5
MQ-131	O_3	6

The sensing platform samples the surrounding air based on cycle timer and writes the measurements to a data packet. The current cycle lasts 3 minutes in which the components MiCs-4514 and MQ131 heat up to $300-500°C$ before powering off for the next cycle. The reported readings include the temperature, humidity, pressure, battery level, UV, particulate matter PM_1,$PM_{2.5}$, PM_4, PM_{10} carbon monoxide (CO), nitrous dioxide NO_2, ozone O_3, and positioning information and a timestamp. Each data packet costs roughly 560 bytes per sample. As samples are transmitted every 3 minutes, each HOPE sensor generates roughly 0.26 Megabytes per day. Scaling up to 100 HOPE sensors results in accumulative data storage of 26 MegaBytes per day.

The HOPE sensor was originally designed to be carried by users for studies of outdoor air quality. To preserve battery while indoors, the units have been programmed to use a long sampling interval when they are stationary, and switch to a shorter interval when they detect that they have been moved. While the units do not report whether they have moved or not, we deduce this from the rate at which they report readings.

Following manufacturing the HOPE[5] sensors were calibrated for CO, NO_2 and O_3 at the University of Helsinki and $PM_{2.5}$ in FMI laboratory in May 2019. The calibrations are illustrated in Figure 3). Four portable devices were further tested by co-location at Helsinki Region Environmental Services (HSY)[6] monitoring site in Mäkelänkatu in Kallio, Helsinki for 10 days. The HOPE device data conversion limits assumes an ambient pressure of 1 atmosphere and a temperature of 25°C. Table II shows the data conversion rates of our HOPE sensor.

Table II: Data conversion limits for HOPE sensors.

Variable	Rate
NO_2	1 ppb = 1.88 μg/m^3
O_3	1 ppb = 2.00 μg/m^3
CO	1 ppb = 1.145 μg/m^3

IV. Use Case

To validate the capabilities of MegaSense CPS to monitor urban air quality and influence citizens to reduce their exposure to air pollution, the system is tested in Helsinki, Finland, as part of the Urban Initiatives Actions HOPE project coordinated by the City of Helsinki. Citizens are loaned portable HOPE sensors to continuously measure their own exposure to air pollution. Combining all citizens data enables creation of district based crowd-source maps.

During data gathering campaigns registered citizens download the HOPE Exposure App from Google play store and tether their Android smart phone to HOPE sensor. The HOPE Exposure App is pre-configured with the MegaSense server address and upon launching the app and switching on the HOPE sensor, measurement data packets including the smartphone GPS location are routed by wireless connection via local mobile service provider to the MegaSense Core.

[5]https://www.uia-initiative.eu/en/uia-cities/helsinki
[6]https://www.hsy.fi/en/residents/pages/default.aspx

Figure 3: HOPE sensor calibration for CO in chamber and co-location calibration at HSY monitoring site in Mäkenlänkatu, Helsinki.

A. MegaSense Core

Citizens measurement data is routed to MegaSense Edge layer Rest API. The measurements are forwarded to buckets (accessed controlled datasets) in MegaSense cloud data storage. MegaSense permissions to access or upload data is controlled on a per-bucket and per-user basis by super users. All HOPE sensor end-user data is stored and collected as raw data in JSON form in an bucket with access key named HOPE. Other sub buckets are created for 3rd parties to ensure privacy. Each authorized entity is given an access key with access to the required buckets, and which can be revoked. HOPE raw data is processed by calibration analytic techniques to improve the accuracy of the sensor data. The calibrated data is stored in the processed data buckets for publishing via the MAP API to end users.

B. External systems

External systems are scraped to augment the HOPE sensor datasets. To differentiate between, indoor air quality measurements and outdoor air measurements, end user HOPE data is combined with a personal mobility app called MOPRIM[7]. The app detects and records the end-users personal mobility using their smartphone sensors [20]. To complement the outdoor ambient concentrations of air pollutants, HOPE sensor data is integrated with open data taken from FMI ENFUSER [21]. ENFUSER data includes meteorological parameters, wind vector data, road traffic data, and pollutant measurements taken from nearest city monitoring stations. It produces hourly concentration of particle matter ($PM_{2.5}$ and PM_{10}) and NO_2 for Helsinki. To display geo-spatial location, the HOPE time series measurements and corresponding GPS records are inserted on top of OpenStreetMaps [22].

C. HOPE Exposure App

Registered citizen use HOPE Exposure App to view their air pollution exposure profile through password protected web access. On the end user web page timestamped data is organized into time series graphs of the previous day's exposure to $PM_{2.5}$, NO_2, CO, O_3, and graphs of last three days of the same pollutants. These air pollution exposure profiles are personal indicators associated with end user carrying the HOPE device and stored as an explicit digital representation of their identity (name, age, address, and GPS location). When the HOPE Exposure App and HOPE Sensor are persistently sampling, the air pollution exposure profile records the end user's air quality in their micro-environment context (residential house) and changes when travelling to the next micro-environment (walking to the bus stop). It enables end user to learn the spatial-temporal context of steady-state exposure conditions (work place) and rapid fluctuations (near busy roads). In the example shown below, $PM_{2.5}$ data is recorded with HOPE sensor connected to a hand bag, sampling 273 data records on 18-11-2019. Table III presents the air pollution exposure characterized by presence in different micro-environments.

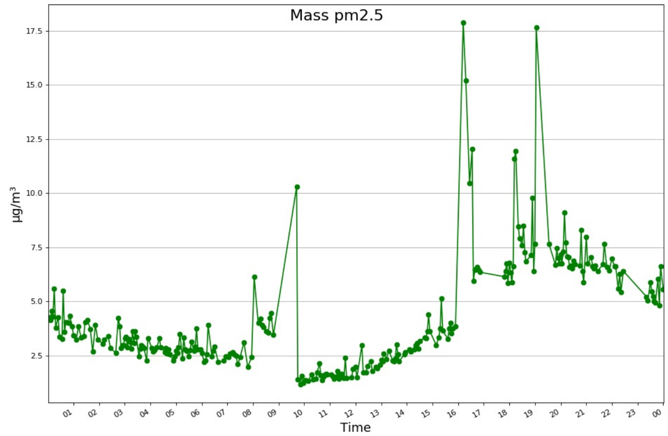

Figure 4: $PM_{2.5}$ air pollution profile for an individual.

Table III: Air pollution exposure profile in different micro-environments.

Time (hour)	Environment
12:00 - 08:00	Indoor residential measurements
08:00 - 10:00	Transport & outdoor micro-environments
10:00 - 16:00	Indoor office micro-environments
16:00 - 19:30	Transport & outdoor micro-environments
19:30 - 00:00	Indoor residential measurements

These micro-environments are evident in the end user's air pollution exposure profile shown in Figure 4 and depict lower $PM_{2.5}$ exposure in enclosed indoor environments, family residential address and university shared research space, and marked increases when walking outside, and within sealed transport micro-environments above-ground bus service and below ground in the metro system. The $PM_{2.5}$ values are typical for Helsinki and below the World Health Organization (WHO)[8] limit values.

Citizens view air pollution exposure profile of a district through the same password protected web access. On their web

[7]https://www.moprim.com/

[8]https://www.who.int/airpollution/publications/aqg2005/en/

page are exposure animations for Air Quality Index, $PM_{2.5}$, NO_2, CO, O_3, of the local district. The animations are a series of time sheets (maps) created by combining $PM_{2.5}$ and gas measurements from all HOPE sensors identified within a predefined spatial and temporal window. The animations show the spatial-temporal distribution of hyper-local pollution hot spots. A pollution hot spot can be caused by wood burning. Although indoor fire or outdoor garden fire are hyper local, small-scale burning of wood is the largest emission source for fine particulate matter in Finland, causing around half of domestic fine particulate matter emission and according to the Finnish Ministry of Environment causes around 200 premature deaths each year.

The example air pollution exposure profile of a district, Pakila, Helsinki, shown in Figure 5 was created by combining all citizens measurements (end user air quality exposure profiles to $PM_{2.5}$) onto hourly space-time slices between 30.10.2019 to 19.11.2019. Pollution hot spots are defined when $PM_{2.5}$ persistently exceeds the WHO limit value (25 $\mu g/m^3$) for all sequential space-time slices, and displayed as red pixels on top of a static OpenStreetMap of the district. The other pixel categories are presented in Table IV.

Table IV: The pixel categories used in Figure 5.

Colour	Value
Red	$> 25\mu g/m^3$
Orange	$18.75\mu g/m^3$
Yellow	$12.5\mu g/m^3$
Light green	$6.25\mu g/m^3$
Green	$2.5\mu g/m^3$

To identify the outdoor hot spots, simple filtering rules are applied such as a temperature threshold (temperature less than 20°C). To fill in missing geo-spatial sampling holes, when end users are not near each other, neighbourhood interpolation is applied on the time slice. To fill in missing temporal sampling holes between each space-time slice, when the end user is not using the HOPE sensor (turned off by app or powered off the HOPE sensor), temporal interpolation is applied between sequential space-time slices.

D. Clean Air Routing Apps

The HOPE project further develops the clean air journey planner application that creates optimal walking and cycling routes based on air quality of Helsinki (Figure 6). The route guide is made by Forum Virium Helsinki.

V. Discussion

MegaSense cyber-physical system for monitoring urban air quality is spatially distributed though deployment of portable scalable low-cost air quality sensors [23]; time-sensitive by providing real-time interaction between the physical atmospheric measurements and end user's receiving air quality information [7]; and multi-scaled making use of edge computing and advanced cloud computing integration with external systems. MegaSense provides a feedback loop between the physical processes (air pollution), cyber computation, and

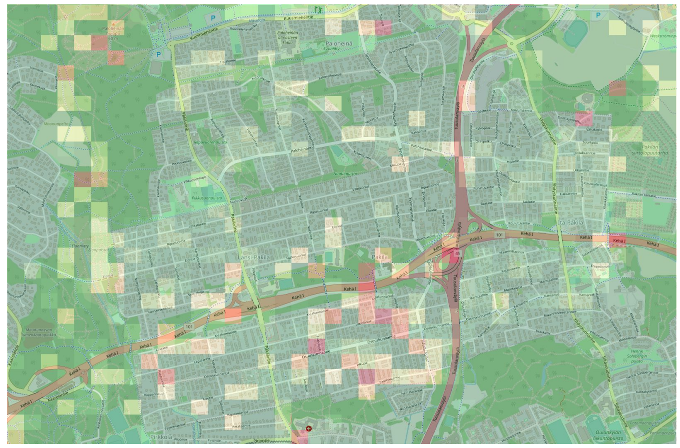

Figure 5: Air pollution profile of a Pakila district in Helsinki.

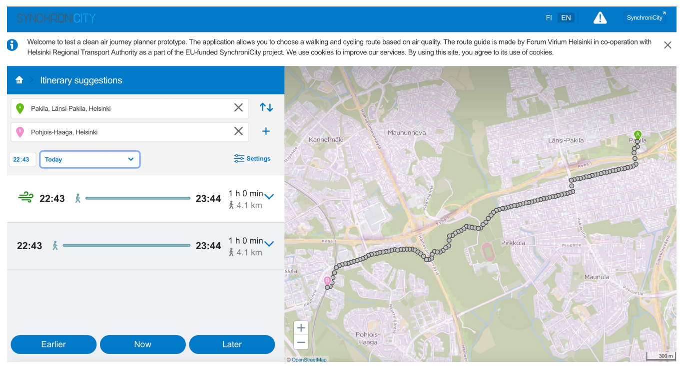

Figure 6: Clean air routing navigation path.

rapid information dissemination to exposure apps. It enables end-users to measure personal exposure to individual air pollutants where-ever they are, when-ever they want to, and create personal intervention measures to reduce the length of exposure in a particular micro-environments. This important for cohorts sensitive to air pollution such as: children [24], sufferers of lung diseases [25] and cardiovascular diseases [26], and the elderly [27]. Agility is increased through the battery-powered, portable low-cost sensor tethered to smart phone, as the CPS service can implemented in any urban environment, city, region or country where connection to the MegaSense cloud or server instance is allowed. Operation and maintenance is transferred to the motivated citizens using portable sensors. When citizens share their air pollution exposure data they contribute to identifying hyper-local pollution hot spots maps in their own districts. This is important for Public Authorities seeking collaborative intervention methods to reduce local air pollution [28].

Improved understanding of local emission sources and concentrations stimulates knowledge representation based navigation tools, clean air routing apps that nudges personal behavioural changes leading to overall improved air quality. Extending the MegaSense CPS feedback loop to mobile platforms such as cooperative drones and autonomous vehicles is the next step. Modifying drones IoT delivery tasks [29] to search and detect air pollution emission sources from fixed urban locations and mobile vessels and mapping in 3D spaces to characterize pollution concentrations at different heights.

The challenges of the current MegaSense CPS that needs addressing: inserting run time configuration updates to portable sensing platforms; optimizing integration to other systems and data fusion; and improving privacy and system security - end user access to their air quality exposure and GPS data is password protected, however security mechanisms against denial of service attacks are yet to implemented and tested.

VI. Conclusion

The MegaSense cyber physical system offers urban citizens a feedback loop to make a difference to their personal exposure to air pollution and related health impacts. It enables citizens to self-monitor urban air quality in homes, work spaces, in vehicles and outdoors. Based on this data, citizens receive advice, history profiles and pollution hot spot maps on their smart devices through exposure apps. This empowers citizens and policy makers to develop air quality solutions to reduce emissions at the local level in their own districts. MegaSense supports the emergence of navigation tools for clean air and health optimal routing applications. Network scaling and real-time performance are supplemented by splitting the system into two logical layers: *Edge* and *Cloud*, Allowing the former to be replicated close the data sources and data users.

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